Automatic Planning Based on Rough Set Tools: Towards Supporting Treatment of Infants with Respiratory Failure

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Abstract. This paper investigates medical planning in the context of a complex dynamical system. The solution to the problem of medical planning is proposed using application of rough set tools for modeling networks of classifiers induced from data and ontology of concepts delivered by experts. Such networks allow us to develop strategies for automated planning of a treatment of infants with respiratory illness. We report results of experiments with the networks of classifiers used in automated planning of the treatment of newborn infants with respiratory failure. The reported experiments were performed on medical data obtained from the Neonatal Intensive Care Unit in the Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow, Poland. The contribution of this paper is an approach to the similarity relation approximation between therapy plans.

Keywords: Automated planning, concept approximation, dynamical system, ontology of concepts, respiratory failure, rough sets, similarity relation approximation.

1 Introduction

This paper investigates medical planning in the context of a complex dynamical system (see, e.g., [1–3]). A *complex dynamical system* (also called as an *autonomous multiagent system* [2] or *swarm intelligent systems* [7]) is a system of complex objects that are changing (adapting), interacting, and learning over time. Such objects (usually linked by some dependencies) sometimes can cooperate between themselves and are able to perform flexible autonomous complex actions (operations, changes). For example, one can consider *road traffic* as a complex dynamical system represented by a road simulator (see, e.g., [2]).

Another example can be taken from medical practice. This second example concerns the treatment of infants with respiratory failure, where a given patient is treated as a complex dynamical system, while diseases of a patient are treated as complex objects changing and interacting over time (see [3] and Section 2).

The prediction of behaviors of a complex object evaluated over time is usually based on some historical knowledge representation used to store information about changes in relevant features or parameters. This information is usually represented as a data set and has to be collected during long-term observation of a complex dynamic system. For example, in case of the treatment of the infants with respiratory failure, we associate the object parameters mainly with values of arterial blood gases measurements and the X-ray lung examination. A single action is often not sufficient for changing the complex object in the expected direction. Therefore a sequence of actions needs to be used instead of a single action during medical treatment. Hence, methods of automated planning are necessary during monitoring of a given complex dynamic system (see [5, 8]).

The contribution of this paper is an approach to the similarity relation approximation between therapy plans. The problem of inducing classifiers for similarity relations is one of the challenging problem in data mining and knowledge discovery. The existing methods are based on building models for similarity relations based on simple strategies for fusion of local similarities. The optimization of the assumed parameterized similarity formula is performed by tuning parameters relative to local similarities and their fusion. However, the similarity relations for real-life problems are complex objects, i.e., their construction from local similarities cannot be obtained by simple fusion functions. Hence, such similarity relations cannot be approximated with the satisfactory quality by employing the existing simple strategies. To support the process of similarity relation approximation, we propose to use domain knowledge represented by concept ontology expressed in natural language. The ontology consists of concepts used by expert in his explanation of similarity and dissimilarity cases. Approximation of the ontology makes it possible to obtain some relevant concepts for approximation of the similarity relation.

This paper is organized as follows. In Section 2, some medical knowledge about the treatment of the infants with respiratory failure is given. The basic concept of a planning rule is given in Section 3. The automated planning of actions for groups of complex objects realized using *planning graphs for a group of objects* is considered in Section 4. The method of estimation of the similarity between two plans is described in the Section 5. Experimental results using the proposed tools for automated planning, are presented in Section 6.

2 Neonatal respiratory failure

New possibilities in medical intensive care have appeared during last decades thanks to the progress in medical and technical sciences. This progress allowed us to save the live of prematurely born infants including the smallest born between 20th and 24th week of gestation with the birth weight above 500g.

The respiratory system dysfunction appearing in the first hours of life and leading to respiratory failure is the most important single factor limiting survival of our smallest patients. The respiratory failure is defined as inappropriate blood oxygenation and accumulation of carbon dioxide and is diagnosed based on arterial blood gases measurements. Clinical symptoms - increased rate of breathing, accessory respiratory muscles use as well as X-ray lung examination are also included in assessment of the severity of respiratory failure.

The most important cause of respiratory failure in prematurely born infants is RDS (respiratory distress syndrome). RDS is evoked by lung immaturity and surfactant deficiency. The other co-existing abnormalities - PDA (patent ductus arteriosus), sepsis (generalized reaction on infection leading to multiorgan failure) and Ureaplasma lung infection (acquired during pregnancy or birth) may exacerbate the course of respiratory failure. Each of these conditions can be treated as a unrelated disease requiring separate treatment. But they also co-exist very often, and in a particular patient we may deal with their combination, for example:

$$\text{RDS} + \text{PDA} + \text{sepsis}.$$

In the holistic therapeutic approach it is important to synchronize the treatment of the co-existing abnormalities, what finally can lead to cure from respiratory failure.

The aim of this paper is to present some computer tool for automated planning of the treatment (see, e.g., [5, 8]). In this approach, a given patient is treated as an investigated complex dynamical system, whilst diseases of this patient (RDS, PDA, sepsis, Ureaplasma and respiratory failure) are treated as complex objects changing and interacting over time (see Section 4). However, the respiratory failure is much more complex than the others. Therefore, the respiratory failure (as a complex object) should be treated as a consequence of several diseases, such as RDS, PDA, sepsis and Ureaplasma. Our task is to make possible an automatic planning (by a computer program) the sequence of medical actions that should be applied for a given patient in order to continue the proper treatment started by the human expert.

It should be emphasized that in general, the automatic planning of the treatment is a very difficult and complicated task. Such activity requires engaging a complex medical knowledge, joined with the sensor information about state of a given patient. However, methods presented by us, allow to obtain quite satisfactory results in the short-term planning of treatment of infants with respiratory failure (see Section 6). One of the reason is that medical data sets have been accurately prepared for purposes of our experiments using the medical knowledge. For example, the collection of medical actions that are usually used during the treatment of infants with respiratory failure, has been divided into a few groups of similar actions (for example: antibiotics, anti-mycotic agents, catecholamines, corticosteroids, hemostatic agents). This was very helpful in the prediction of actions because the number of actions was significantly decreased.

3 The automatic planning for complex objects

In this research, we discuss some rough set [6] tools for automated planning as part of a system for modeling networks of classifiers. Such networks are constructed using an ontology of concepts delivered by experts[1].

The basic concept we use is a *planning rule*. Planning rules are proposed by human experts on the basis of domain knowledge and are defined as following formula: $state\ before\ action \rightarrow action \rightarrow state\ 1\ after\ action\ or\ ...\ or\ state\ k\ after\ action$, where $state\ before\ action$ is a description of state of the complex object before execution of action, $action$ is some kind of action that can be applied for the given complex object and $state\ 1\ after\ action$, ..., $state\ k\ after\ action$ is the collection of states, that can be observed as a consequences of the action. It is easy to see, that the planing rule can be used to change the state (from the left hand side of the rule) to another state of the complex object (on the right hand side of the planning rule). However, the result of applying such rule is often nondeterministic. Hence, there are usually many states on the right hand side of the planning rule. A set of planning rules can be represented by a *planning graph*. There are two kinds of nodes in planning graphs: *state nodes* represented by ovals and *action nodes* represented by rectangles (see, e.g., Fig. 1). The connections between nodes represent temporal dependencies, e.g., the connection between the state node s_1 and the action node a_1 says, that in the state s_1 of the complex object the action a_1 can be performed whilst the connection between the action node a_1 and the state node s_2 means, that after performing action a_1 in s_1 the the status of the complex object can be changed from s_1 to s_2. Figure 1 shows how planning rules can be joined in order to obtain a planning graph.

Notice, that any state from the planning graph can be treated as a complex concept, specified by a human expert in the natural language. Such concepts can be approximated by approximate reasoning schemes (AR-schemes, for short) using data sets and the domain knowledge accumulated for the given complex dynamical system (see [1–3]). Hence, it is possible to identify the initial state at the beginning of planning for the considered complex object.

The output for the planing problem for a single complex object is a path in the planning graph from the initial node-state to the *expected (target) node-state*. Such a path can be treated as a plan of action that should be performed beginning from the given complex object in order to change its state to the expected status.

In practice, it is very often that the generated plan has to be compatible with the plan proposed by a human expert (e.g., the plan of treatment should be compatible with the plan of the treatment suggested by medical experts). It is strongly recommended, that the method of the verification and evaluation of generated plans should be based on the similarity between the generated plan and the plan proposed by human experts (see Section 6). Hence, the usage of special tools, that allow as to resolve conflicts (nondeterminism) of actions in

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[1] The ontology focuses on bases for concept approximation (see, e.g., [4]).

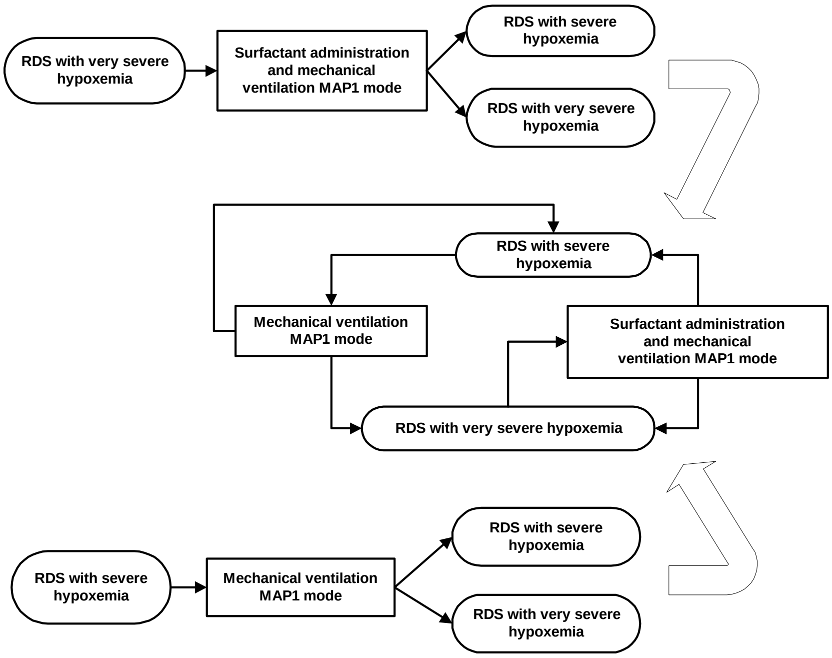

Fig. 1. Two exemplary planning rules and their composition into the planning graph

planning rules is needed. Therefore, in this paper we propose a family of classifiers constructed for all state-nodes from the planning graph separately. These classifiers are constructed on the basis of decision rules (with minimal number of descriptors) computed for a special decision table, called a *resolving table*. The resolving table is constructed for any state-nodes from the planning graph and stores information about objects of a given complex dynamical system satisfying the concept from the current state-node. Any row of this table represents information about parameters of a single object registered at a given a time point. Condition attributes (features) from this table are defined by human experts and have to be computed on the basis of information included in the description of current state of the complex object as well on some previous states or actions obtained from the near or far history of the object. It should be emphasized, that the definition of such condition attributes should allow us for an easy update of their values during the construction of a given plan according to performed actions and obtained new states of complex object. This property allow us for some kind of simulation during the process of the plan construction. The decision attribute of the resolving table is defined as the action that has been performed for a given training object, joined with the status obtained as an real effect of usage this action for this object. Next, we construct rule based classifiers for all states, i.e., for all associated resolving tables. In addition, these classifiers allow us to obtain the list of actions and states obtained after performing them together with their weights in descending order. This is very important for generation of plans for a group of objects (see Section 4). In planning for a single object the action with the highest weight is chosen.

4 The automatic planning for groups of complex objects

In this section we present some generalization of the method for automated planning described in Section 3. For a group of objects we define a graph that we call as a *planning graph for a group of objects*. Similarly to the planning graph for a single object (see Section 3), there are two kinds of nodes in this graph. *States nodes* (denoted by ovals) represent the current state of group of objects and are specified as complex concepts by a human expert in the natural language. *Action nodes* (denoted by rectangles) represent so called *meta actions* defined for groups of objects by a human expert too. Meta actions are performed over a longer period called a *time window* [2].

In Figure 2, we present an exemplary planning graph for a group of four diseases: sepsis, Ureaplasma, RDS and PDA, related to the planning of the treatment of the infant during the respiratory failure. This graph was created on the basis of observation of medical data sets (see Section 6) and with support of human experts. There are 4 state nodes and 10 action nodes in this graph. Connections represent spatio-temporal dependencies between states and actions. For example, after the node "Severe respiratory failure" the meta action "Improvement of respiratory failure from severe to moderate" can be realized for a given patient and as an effect of this meta action we observe the state "Moderate respiratory failure".

Notice, that any state-node from a planning graph for groups of objects can be treated as a complex concept, that is specified by a human expert in the natural language. Such concepts can be approximated by AR-schemes using data sets and the domain knowledge accumulated for the given complex dynamical system (see [1–3]). Thanks to that, it is possibly to recognize the initial state at the beginning of planning for the considered group of complex objects.

Similarly to the single complex object, during planning for some group of complex object the path in the planning graph from the initial node-state to the target node-state should be found. However, any action from such constructed path should be checked on the lower level, i.e., on the level of any member of the group separately, if such action can be realized in practice in case of particular member of this group. In other words, it means that for any member of the group the sequence of action should be planed in order to obtain meta-action on the level of the groups of objects.

At the beginning of the planning for the group of objects we assign the current state of the group of objects. As it was mentioned before, it can be done by AR-schemes that have been constructed for all states from the planning graph. Next, we plan a sequence of actions that can transform the group of objects from the current state to the target state (more expected, safer or more comfortable). For example, in the case of the treatment of infants with respiratory failure, if the

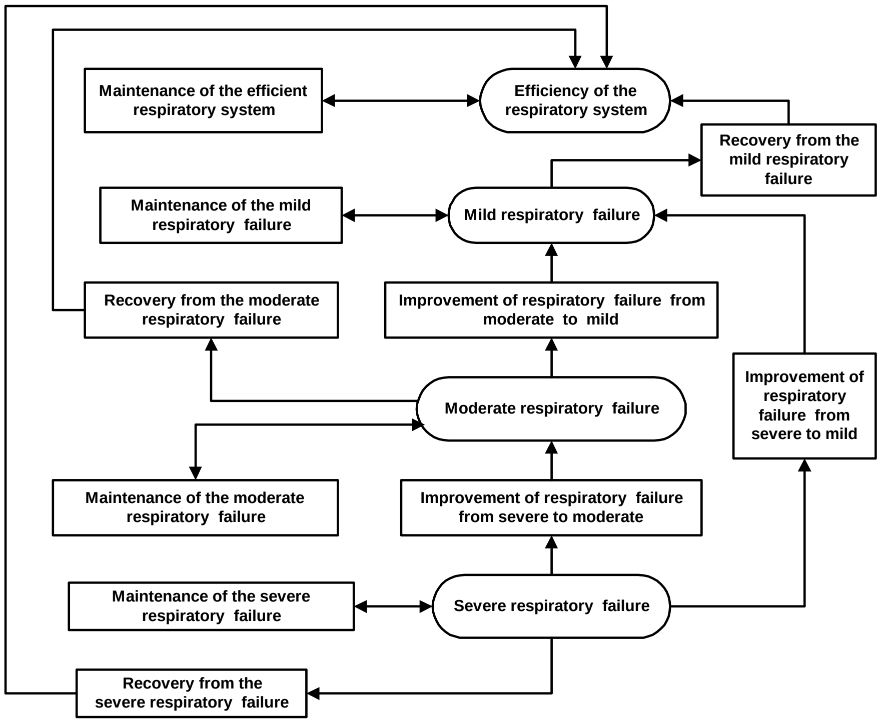

Fig. 2. A planning graph for the treatment of infants during the respiratory failure

infant is with the severe respiratory failure, then we try to change the patient status using some methods of treatment in order to change his status to the moderate or mild respiratory failure (see Figure 2).

So, our system can propose many plans on the basis of connections from the planning graph for groups of objects, starting from the current state. Next, the system can chose only one plan, that seems to be the most effective. However, it is necessary to guarantee that the proposed plan can be realized on the level of any object belonging to the group. In other words, for any object from the group the specific plan should be constructed in order to realize a given meta action from the level of the group. Besides, all constructed plans for objects belonging to group should be compatible, i.e., they can coexist between themselves. Therefore during planning a meta action for the group of objects we used the special tool for verifying of the compatibility of plans generated for all members of the group. The verification of the compatibility of plans generated for members of the group can be performed by using some special decision rules (with minimal number of descriptors), that we call as *elimination rules*. Such rules make it possible to eliminate such combination of plans generated for members of groups, that are not compatible from the point of view of the domain knowledge. This is possible, because such rules describe all important dependencies between plans, that are joined together. If the combination of plans is not consistent with any elimination rule then this combination is eliminated and cannot be used for realizing the meta action from the level of group of objects. The set of elimination rules can be specified by human experts or can be computed from data sets. In both these cases we need the set of attributes (features) defined for single plan that are used for the explaining of elimination rules. Such attributes are specified by human experts on the basis of domain knowledge and they describe some important features of the plan (generated for single complex object) from the point of view the proper joining this plan with plans generated for other members of the group. For example, in case of the treatment of infants with respiratory failure, such attributes can concern medicines that were used for the treatment of a given patient or some states that were observed during treatment of a given patient.

These features are used as a set of attributes in the special table that we call *an elimination table*. Any row of the elimination table represents information about features of plans assigned for complex objects belonging to the exemplary group of objects from the training data. We propose the following method of calculation the set of elimination rules on the basis of the elimination table. For any attribute from the elimination table, we compute the set of rules treating this attribute as a decision attribute. In this way, we obtain the set of dependencies in the elimination table explained by decision rules (with minimal number of descriptors). In practice, it is necessary to filter such obtained elimination rules in order to remove the rules with the low support, because such rules can be too strong matched to the training data. As we said before, the set of elimination rules can be used as a filter of not consistent combinations of plans generated for members of groups. Any combination of plans is eliminated when exists an elimination rule, that is not supported by features of this combination, whilst the combination matches to the predecessor of this rule. In other words, the combination of plans is eliminated when the combination matches to the predecessor of some elimination rule and does not match to the successor of this rule.

If the combination of plans for members of the group is consistent (it was not eliminated by elimination rules), we should check if the execution of this combination allow us to achieve the expected meta action from the level of group of objects. It can be done by a special classifier constructed for a table called as an *action table*. The structure of the action table is similar to the structure of the elimination table, i.e., attributes are defined by human experts and rows represent information about features of plans assigned for complex objects belonging to the exemplary group of objects from the training data. However, we add to this table a decision attribute. Values of the decision attribute represent names of meta actions which will be realized as an effect of the execution of plans described in the current row of this table (in the training table). The classifier computed for the action table allow us to predict the name of meta action for the given combination of plans from the level of members of group. It is the last step of selection such combination of plans, that allow us to obtain the target meta action from the point of view the group of objects.

It was mentioned in Section 3 that the resolving classifier used for the generation of a next action during the planning for a single object, gives us the list of actions (and states after usage of action) with their weights in descending order. It allow us to generate many alternative plans for any single object and many alternative combination of plans for the group of objects. Therefore the chance of finding the expected combination of plans from the lower level in order to realize a given meta action (from the higher level) is relatively high.

After planning the selected meta action from the path of action from the planning graph (for a group of objects), the system begins the planning of the next meta action from this path. The planning is stopped, when the planning of the last meta action from this path is finished.

5 Estimation of the similarity between plans

If we want to compare two plans, for example the plan generated automatically by our computer system and the plan proposed by human expert, we need a tool to estimate the similarity. This problem can be solved by putting some mathematical formula, that can be used for computing of numerical values of similarity between plans. For example, in case of our medical data (see Section 2 and Section 6), such formula can compute a similarity between two plans as the arithmetic mean of similarity between all corresponding pairs of actions (nodes) from both plans, where the similarity for the single corresponding pair of actions is defined as a consistence measure of medicines and medical procedures expressed by these actions. However, one can observe that such an approach seems to be very abstract and arbitrary, because it does not take into account the domain knowledge on similarity of plans.

According to the domain knowledge, it is quite common, that there are many aspects of similarity between plans. For example, in case of comparison of medical plans used for the treatment of infants with respiratory failure, we should take into consideration, e.g., the similarity of the antibiotics use, the ventilation mode and the similarity of PDA closing. Moreover, every aspect of the similarity should be understood in a different way. For example, in estimation of the similarity in the antibiotic treatment, it should be evaluated the kind of antibiotic, as well as the time of administration. Therefore, it is necessary to investigate and take into account all incompatibilities of the antibiotic use between corresponding pairs of nodes from both plans. Excessive doses are rather acceptable (based on expert knowledge), whilst the lack of medicine (if it was necessary) should be taken as a very serious mistake. In such situation, the difference in our assessment is estimated as very significant. A bit different interpretation of similarity should be used in case of the ventilation. As in antibiotic use, we investigate all incompatibilities of the ventilation mode between corresponding pairs of nodes from both plans. However, sometimes, according to expert knowledge, we simplified our assessments, e.g., spontaneous respiration and CPAP were estimated as similar. More complicated situation is present if we want to judge the similarity in treatment of PDA. We have to assign the ventilation mode, as well as the similarity of PDA closing procedure. In summary, any aspect of the similarity between plans should be take into account in the specific way and the domain knowledge is necessary for joining all these similarities (obtained for all aspects). Therefore, the similarity between plans should be assigned on the basis of a special ontology specified in a dialog with human experts.

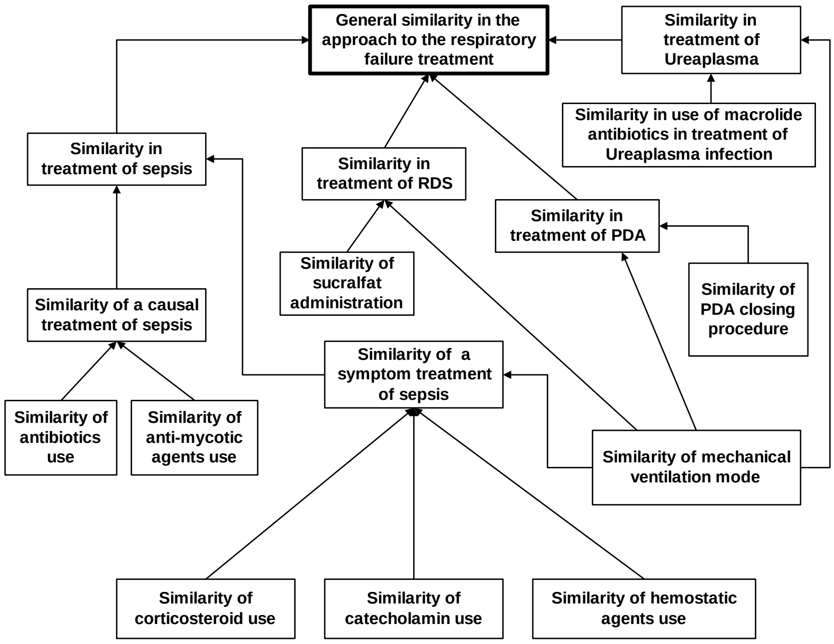

Fig. 3. An exemplary ontology of similarity between plans of the treatment of newborn infants with respiratory failure

The Figure 3 shows an exemplary ontology of similarity between plans of the treatment of newborn infants with the respiratory failure. This ontology has been provided by human experts. However, it is also possible to present some other versions of such ontology, instead of that presented above, according to opinions of some other group of human experts.

Using the ontology presented in Figure 3, we developed methods for inducing hierarchical classifiers predicting the similarity between two plans (generated automatically and proposed by human experts). The methods for construction of such classifiers are based on AR schemes and were described in [1].

It is important to mention that besides the ontology, experts usually should provide an exemplary data (values of attributes) for the purpose of concepts approximation from the ontology (see, e.g., [1] for more details).

6 Experimental Results

To verify the effectiveness of presented in this paper methods of automated planning, we have implemented the algorithms in a *Automated Planning* library (AP-lib), which is an extension of the RSES-lib 2.1 library forming the computational kernel of the RSES system[2].

The experiments have been performed on the medical data sets obtained from Neonatal Intensive Care Unit in Department of Pediatrics, Collegium Medicum, Jagiellonian University, Cracow. The data were collected between 2002 and 2004 using computer database NIS (Neonatal Information System). The detailed information about treatment of 340 newborns are available in the data set, such as perinatal history, birth weight, gestational age, lab tests results, imagine techniques results, detailed diagnoses during hospitalization, procedures and medication were recorded for the each patient. The study group included prematurely born infants with the birth weight $\leq 1500g$, admitted to the hospital before end of the 2 day of life.

In our experiments, we used one data table extracted from the NIS system, that consists of 11099 objects. Each object of this table describes parameters of one patient in single time point. There were prepared 7022 situations on the basis of this data table, when the plan of treatment has been proposed by human experts during the realistic clinical treatment.

As a measure of planning success (or failure) in our experiments, we use the special hierarchical classifier that can predict the similarity between two plans as a number between 0.0 (very low similarity between two plans) and 1.0 (very high similarity between two plans). This classifier has been constructed on the basis of the ontology specified by human experts and data sets (see Section 5 and Figure 3). The methods of construction such classifiers are based on AR schemes and were described in [1]. We use this classifier to determine the similarity between plans generated by our methods of automated planning and plans proposed be human experts during the realistic clinical treatment. A training set consists of 4052 situations (when plans of treatment have been assigned), whereas a testing set consists of 2970 situations, when plans have been generated by automated method and expert plans were known (in order to compare both plans). The average similarity between plans for all tested situations was about 0.82 whilst the coverage of tested situation by generated plans was about 88 percent.

7 Conclusion

In this paper, we discussed some rough set tools for automated planning that are developed for a system for modeling networks of classifiers. The performed experiments show that the similarity between the plan of treatment generated automatically and the plan proposed by human experts during the real clinical

[2] See RSES Homepage at `logic.mimuw.edu.pl/∼rses`

treatment is sufficiently high. Therefore we conclude that our methods have promise as useful tools in medical practice. In our further work, we would like to increase the recognition of similarity between plans of the treatment (generated automatically and proposed by human experts) and to improve the coverage of tested situations by the generated plans.

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